

RESEARCH ARTICLE

Trail vs. thicket: Evaluating conservation detection dog performance in varied terrain

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Funding information

Florida Fish and Wildlife Conservation
Commission, Grant/Award Number:
Nongame Wildlife Trust Fund

Abstract

Use of detection dogs has emerged as an effective survey method for rare and cryptic species, outperforming traditional methods. However, there is little information available on how survey conditions may affect survey efforts. This study investigates the detection probability, effective sweep width, and search time of a detection dog working on-lead in varying vegetation and weather conditions in Florida. We established 4 200-m long transects in habitats with varying vegetation structure: open field, open canopy forest, closed canopy forest, and trail. American mink (*Neogale vison*) scat was set along each transect, in locations unknown to the detection dog handler, at distances ranging from 0 to 24 m from the transect. Vegetation and weather conditions were recorded for each survey. Between August 2021 and October 2022, we conducted 28 surveys (112 total transect surveys). Across all transects the detection dog located 66% of hidden scats ($n = 384$). We calculated an effective sweep width of 49 m (24.5 m on either side of the transect) and detection probability decreased with distance from transect line. Contrary to expectations, vegetation structure and weather conditions did not influence detection probability, but vegetation structure did affect search time, an important variable to consider when designing surveys. Search time increased with increases in understory vegetation obstruction and basal area. Conducting surveys on trails showed promise as an effective search method, having

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similar detection probability to off-trail transects and faster search times than the closed canopy forest transect. Trail surveys may be particularly useful for areas that would otherwise be impassable, but their effectiveness may vary based on the target species' behavior. Our study underscores the importance of understanding search metrics in conservation detection dog surveys to design effective and appropriate surveys for anticipated field conditions.

KEYWORDS

detection dog, detection probability, effective sweep width, Florida, trail survey

The study of rare and endangered animals is a critical component of conservation biology; however, it is often hampered by difficulties in detecting these species. Common passive methods for detecting wildlife (e.g., camera traps, track plates, and hair snares) often fail to detect cryptic species with large home ranges or, when paired with attractants, bias sampling efforts by luring the animal to the site (Gorman and Trowbridge 1989, Long et al. 2007a, MacKay et al. 2008). Using scat detection dogs (hereafter referred to as detection dogs) is an active survey method that has outperformed traditional survey methods for rare mammals (Long et al. 2007a, b; Tom 2012). Detection dogs are more likely to provide spatially unbiased sampling (MacKay et al. 2008) and can target multiple species over large areas (Wasser et al. 2004, Long et al. 2007b, MacKay et al. 2008). The use of detection dogs is growing in popularity because of these advantages, but there is limited knowledge of how detection dog surveys are affected by vegetation structure and weather conditions, which can vary widely both spatially and temporally. By understanding how survey conditions affect detection probability, biologists can account for potential limitations and improve study design.

Most studies assessing detection probability have been conducted in open-field settings and do not represent the conditions in which many detection dogs will be working (Cablk et al. 2008, Glen et al. 2018). Several studies have recognized this shortfall and recommended that future studies test detection probability under a variety of vegetation conditions (Cablk et al. 2008, Reed et al. 2011, Glen et al. 2018). Vegetation can interrupt the scent cone of vapor molecules emanating from the target, reducing the distance the scent can travel, and can cause the vapor molecules to pool (e.g., settle in a depression) or swirl (Osterkamp 2020). Pooling and swirling may increase the time necessary for the detection dog to locate the target and reduce the probability of detection (Syrotuck 1972, Rebmann et al. 2000, MacKay et al. 2008). The only study to assess detection dog performance across a variety of vegetation conditions reported that the detection dog performed equally well in all habitats but required additional search effort (i.e., time) in habitats with greater vegetation complexity (Leigh and Dominick 2015).

Weather conditions (e.g., wind direction, wind speed, humidity, and temperature) are typically recorded during detection dog surveys, but their effects are not often empirically tested, and results have been inconsistent (Cablk and Heaton 2006, Long et al. 2007b, Nussear et al. 2008, Reed et al. 2011, Woollett et al. 2015). Generally, moderate winds (2.2–4.5 m/s), mild temperatures (0–18°C), and humidity (> 20%) are thought to improve detection probability, while calm or gusty winds, extreme temperatures, and low humidity are reported to lower detection probability (Osterkamp 2020). Some studies have reported convection turbulence (i.e., air rising from the sun heating the ground) disrupts the scent plume and reduces the detection probability (Graham 1994, Chiacchia et al. 2015), while others have reported that only the number of days since precipitation was influential (Reed et al. 2011). Reed et al. (2011) recommended that future studies using detection dogs examine air temperature, humidity, wind conditions, and local environmental factors (e.g., topography and vegetation composition).

Lastly, when conducting a survey, the search method may impact detection probability or create biases in the survey design. Detection dog surveys are often conducted by searching the environment systematically along transects or grids (Long et al. 2011, Wasser et al. 2012) or by following existing trails, roads, and natural breaks in vegetation (Smith et al. 2005; DeMatteo et al. 2009, 2014). Detection dogs can quickly and efficiently survey a trail and the habitat on either side. Trails may be advantageous when searching for rare and cryptic species, particularly those with undefined distributions or habitat associations, or when the potential search area may be too large to thoroughly survey (Baxter and Possingham 2011, Glen and Veltman 2018). Further, trails provide an opportunity to efficiently search areas that might otherwise be impassable (e.g., thick vegetation, marshy areas, or rough terrain) without tiring the dog or handler (MacKay et al. 2008, Glen and Veltman 2018). Although trail surveys have the potential to introduce bias by limiting accessible habitats or excluding species that avoid trails (Cusack et al. 2015, Willcox et al. 2019), they may be a reasonable alternative method for assessing species presence. However, it is unknown if trail surveys affect the searching behavior of the detection dog (e.g., reduced search area). To the best of our knowledge, no studies have compared the effectiveness of on-trail and off-trail detection dog surveys.

Detection probability and effective sweep width (hereafter referred to as sweep width) are important aspects of detection dog studies and are metrics for evaluating the performance of a detection dog team. Detection probability evaluates the likelihood the detection dog will locate the scat, given it is present, whereas sweep width evaluates the area the dog is able to search in one pass, covering either side of a transect (Frost 2000, Cacho et al. 2007, Glen and Veltman 2018, Glen et al. 2018). These metrics can only be evaluated by conducting controlled trials, where scats are set along a survey route. Sweep width is calculated by determining the distance at which the number of missed detections inside the search range equals the number of positive detections outside the search range (Koopman 1946, 1980). The sweep width is directly related to the probability of detection of the target and is useful for establishing survey protocols (Koopman 1946, Glen et al. 2018). For example, by understanding the sweep width and how it may vary in different habitat conditions, researchers can quantify the area likely searched during a survey or determine the appropriate distance between transects to achieve full coverage of an area. Several detection dog studies have assessed sweep width or detection probability of study targets (Long et al. 2007a, Cablk et al. 2008, Reed et al. 2011, Cristescu et al. 2015, Glen et al. 2018), but numerous factors affect these values (e.g., target scat size, age, and decomposition and the particular dog). By increasing the number of studies estimating detection probability and sweep width, generalizations may be possible for future surveys with similar conditions.

In this study, we assess the detection probability, sweep width, and search time of a detection dog working on-lead in Florida. We compare these metrics in varying vegetation and weather conditions and between surveys conducted on- and off-trail. The varying levels of vegetation complexity are assumed to affect air movement differently at the ground level and the ease of movement for the handler and detection dog while searching. Because increasing vegetation density has the potential to interrupt a scent cone, we predict the probability of detection will be greatest in open field settings and decrease as vegetation density increases. Conditions in Florida are hot and humid, often with dense vegetation, and represent an environment not typically tested in detection dog surveys. This study will enhance our understanding of the efficacy of using conservation detection dogs under various survey conditions and build upon existing knowledge of working dogs in different contexts.

STUDY AREA

This study was conducted within a 1-km² area in Newnan's Lake Conservation Area and private inholdings in Alachua County, Florida, USA (29.696255 N, -82.193472 W; Figure 1). The region has a subtropical climate, characterized by a hot and humid rainy season from summer to fall and a cool dry season from winter to spring (Myers and Ewel 1990). The elevation at the site was 28 m above sea level with flat topography. Dominant habitat within this area included an open grass field, mesic flatwoods, and a forested wetland (Florida Cooperative Land

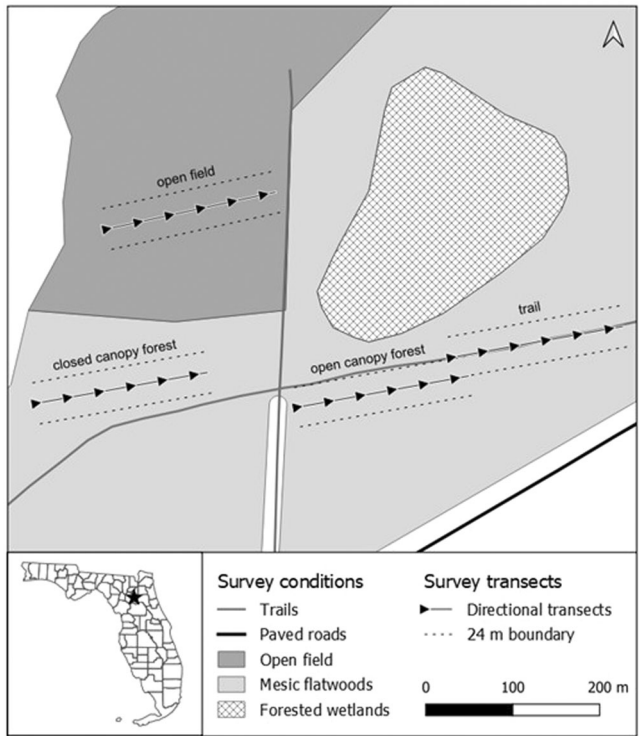


FIGURE 1 Locations and Florida Cooperative Land Cover Map habitat classifications of 200-m long transects within Newnan's Lake Conservation Area and private inholdings. Detection dog surveys were conducted along transects between August 2021 and October 2022 in Florida, USA.

Cover Map; Figure 1). The open grass field was maintained by a private organization and routinely mowed throughout the study. Typical mesic flatwoods are characterized by open canopy pine forests with low shrubs (e.g., saw palmetto [*Serenoa repens*], *Vaccinium* spp., *Lyonia* spp.) and an herbaceous layer primarily composed of grasses (e.g., wiregrass [*Aristida stricta*], dropseeds [*Sporobolus* spp.], panicgrasses [*Panicum* spp.], and broomsedges [*Andropogon* spp.]; Florida Natural Areas Inventory 2010). However, patches within our study area were severely overgrown, having a nearly closed canopy, dense midstory, and a fairly barren ground floor (Figure 2).

METHODS

Establishing transects and scat placement

To assess the effect of vegetation structure on detection probability and sweep width, we established 4 200-m long transects representing different vegetation structures: open field, open canopy forest, closed canopy forest, and trail (Figure 2). An open field transect was established in the grass field and the remaining 3 transects were established in mesic flatwood habitat. We established the open canopy forest transect in an area with typical mesic flatwoods and established the closed canopy forest transect in an area of overgrown mesic flatwoods. We established the trail transect along a 3-m wide grass trail, where conditions varied between traditional and overgrown mesic flatwood habitat on either side of the trail. Vegetation characteristics for each transect were summarized from measurements taken at the location of each placed scat (Table 1). Transects were established within a 1-km²

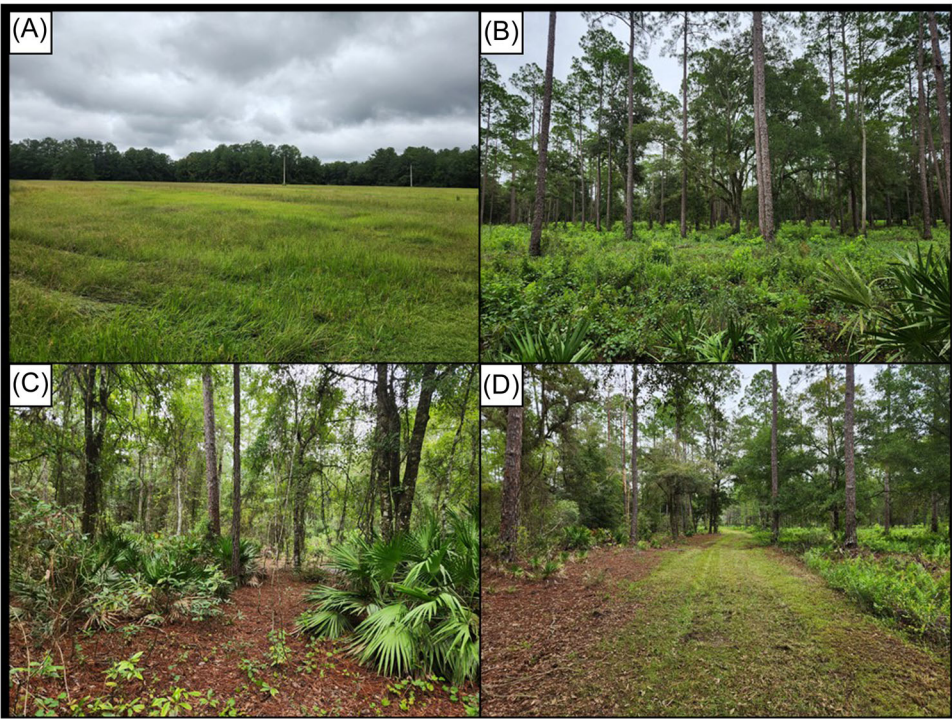


FIGURE 2 Detection dog surveys were conducted along 4 200-m long transects representing different vegetation structures. An open-field transect was established in an open grass field (A); an open canopy forest transect was established in mesic flatwoods (B); a closed canopy forest transect was established in overgrown mesic flatwoods (C); and a trail transect was established along a trail bordered by both mesic flatwoods and overgrown mesic flatwoods (D). Surveys were conducted between August 2021 and October 2022 at Newnan's Lake Conservation Area in Florida, USA.

TABLE 1 Summary of vegetation obstruction, canopy cover, and basal area for each transect type established for detection dog surveys. Measurements were collected at the site of each scat placed within the respective transect and averaged for the transect. Surveys were conducted between August 2021 and October 2022 in Florida, USA.

Transect	Vegetation obstruction (cm)		Canopy cover (%)		Basal area (m ² /ha)	
	Mean	SE	Mean	SE	Mean	SE
Open field	15.4	0.8	0.02	0.01	1.3	0.5
Open canopy forest	28.6	2.7	0.58	0.04	55.5	3.1
Closed canopy forest	23.6	2.5	0.70	0.03	65.3	3.4
Trail	33.7	3.2	0.63	0.03	59.2	2.5

area to allow for comparison of weather variables across all transects (e.g., humidity, temperature) and to limit the variability of any environmental factors (e.g., topography, elevation, vegetation composition). Similarly, the orientation of the trail was used to establish the orientation of all transects so that wind conditions would be comparable across all transects.

American mink (*Neogale vison*) scat (~1-cm diameter) was used as the target in our study for its small size and ease of collection. Mink scat was collected by Zoo Montana and the San Antonio Zoological Society so that each sample was one normal defecation for a captive mink. Scats were kept frozen (~18°C) when not in use. Because this study involved working the detection dog on a 6-m-long lead, we initially designed the study area boundary to be 18 m (i.e., 3 times the length of the detection dog's lead), but because of a high detection rate this was later expanded to 24 m (i.e., 4 times the length of the lead). For each survey, we used the random points inside polygons tool in QGIS (v. 3.16.9 Hannover; QGIS.org 2020) to randomly generate 3 or 4 locations for scat placement, ≥ 24 m apart, within the survey boundary for each transect (Cablík et al. 2008, Glen et al. 2018). We randomized the number of scats placed to reduce any bias that might come from the handler knowing the total number of targets per transect. Similarly, the handler was unaware of the locations of placed scats. Scats were placed in the survey area by another biologist ≥ 30 min prior to the start of a survey. During placement, the biologist walked a circuitous route to reduce the chance of the dog following a human scent trail to the scat (Glen et al. 2018). Scats were used multiple times throughout the study period. The number of uses was included as a variable in analyses to account for any degradation of samples.

At the location and time of each scat placement, we measured canopy cover, basal area, and vegetation obstruction. Canopy cover was estimated at each sampling point by averaging 5 readings taken with a sighting tube, including 1 reading at the center of the point and 4 readings approximately 4-m away in each cardinal direction (Emlen 1967, Ganey and Block 1994). We measured the basal area from the center of each sampling point using a wedge prism with a basal area factor of 10 (Richardson 1958, Warren 1960). We used a 1.5-m Robel pole (marked at 10-cm increments) to measure vegetation obstruction surrounding the sampling point by erecting the pole at the center and taking readings from each of the 4 cardinal directions (Robel et al. 1970). Readings were taken from 4 m away and averaged for the sampling point. Distance from the transect and position (north or south of the transect) were determined post-survey using the Distance matrix function in QGIS (v. 3.16.9 Hannover; QGIS.org 2020). For each transect, we calculated the mean ($\pm$ SE) canopy cover, basal area, and vegetation obstruction of all sampled points to summarize the vegetation conditions in each habitat type.

Transect surveys

The detection dog, a 5-year-old male golden retriever, was trained by Scentworx, Inc. (Alachua, FL, USA) to detect the scat of mink, long-tailed weasels (*Neogale frenata*), and eastern spotted skunks (*Spilogale putorius*). The detection dog and handler worked together for >1 year prior to the start of this study, successfully locating target scats in remote wilderness areas of Florida. During each survey, the handler worked the detection dog from west to east along the transect. If the dog showed interest beyond the length of the 6-m lead (i.e., observed change in focus, speed, or direction), the handler followed the dog out until he was no longer actively searching or exceeded the search boundary. If the dog located a scat, he alerted the handler to the location by sitting, after which he would be rewarded with a toy and play for 1–2 min. A piece of kibble was given in exchange for the toy at the end of the play session. After actively searching an area or locating a scat, the handler guided the dog back to the transect to continue searching from west to east. During each survey, the detection dog wore a Garmin Alpha 100 GPS collar (Garmin Ltd., Olathe, KS, USA) with a 1-sec upload frequency to track the dog's movements along the transect and later calculate the dog's distance searched (linear ground coverage during a survey), time moving (time searching, not including time spent resting or being rewarded for a successful find), and movement speed (time moving divided by distance searched).

All 4 transects were surveyed between 0830 and 1330 on each survey occasion, with transect order rotated on each occasion. This time frame was chosen to avoid working the dog in extreme temperatures and to allow for comparability between surveys. Because of the proximity of the open canopy forest transect and trail transect, these surveys were never conducted consecutively. The detection dog was given a ≥ 30 -min break between surveys, during

which time any missed scats from completed surveys were collected. We waited at least 2 days between survey occasions to reduce the likelihood of the detection dog locating residue from previously placed scats.

At the start and end of each survey, we recorded the time, temperature, relative humidity, wind speed, wind direction, solar insolation (i.e., bright, faint, invisible), and vertical sun angle (i.e., estimated to be $>60^\circ$, $35\text{--}60^\circ$, $15\text{--}35^\circ$, or $<15^\circ$). We measured temperature and wind conditions using a Kestrel 3000 Weather Meter paired with a Kestrel Basic Series Vane Mount (Kestrel Meters, Boothwyn, PA, USA) and compass. We used wind speed, solar insolation, and vertical sun angle to calculate a convection value following the chart adapted from Graham (1994) by Chiacchia et al. (2015), where values range from 1 (weakest convection strength) to 4 (maximum convection strength). Values recorded at the start and end of each survey were averaged to generate one value for each survey to be used in the analysis.

Statistical analyses

We used descriptive statistics to summarize weather conditions recorded before and after each survey and habitat conditions for each transect. We used multiple approaches to quantify detection dog performance. First, to understand the detection rate for each scat placed, we used an exponential decay function to model the assumed relationship between detection and increasing distance from the transect line, where each potential detection was treated as a draw from the Bernoulli distribution. The relationship between the variables can be described by the following equations:

$$p_i = \exp(-\lambda_i \cdot \text{distance}_i)$$

$$\ln(\lambda_i) = \alpha + b_1(\text{covariate}_1) + b_2(\text{covariate}_2) + \dots + b_n(\text{covariate}_n) + \text{trial}_i$$

where p_i is the probability of detection for scat in trial i , distance is the distance from the transect line for scat in trial i , and λ is modeled as a log-linear function of fixed and random effects influencing detection probabilities in date i , where α is the intercept, b_1 to b_n are the effects of covariates of interest on log-lambda and trial_i is a random effect for sampling trial (Hauser et al. 2022).

We fit 14 separate models for each variable of interest to understand patterns in the scat detection data. Variables included in models were habitat type (open field, open canopy forest, closed canopy forest, and trail), scat placement (north or south of the transect line), wind speed, wind working direction (1 if the wind was moving in the direction of scat placement or in multiple directions and a 0 if the wind was moving in the opposite direction of scat placement or not at all), vegetation obstruction, percent canopy cover, basal area, scat age (number of times used prior), search order, average temperature, humidity, convection, average moving speed, and year (Table 2). A single model in our set included the additive influence of wind speed and wind working direction as we assumed that wind working direction would not impact scat detection when wind speed was low or when no wind was present. Log-linear parameters whose 95% credibility interval estimates did not overlap 0 were considered as variables impacting scat detection, whereas all other variables were considered imprecise. We used effect size and precision of parameters to determine the best explanatory model.

We fit models using jagsUI (Kellner 2015) implemented in program R (v. 4.0.3; R Core Team 2020), which uses Bayesian Markov chain Monte Carlo methods. We used diffuse normal priors for the intercept and linear predictors and inverse-gamma priors for the random effect precision parameter. Three chains for 800,000 iterations with 80,000 burn-in iterations were used. We assessed convergence by evaluating trace plots and examining Gelman-Rubin statistics (Gelman et al. 2013), $\hat{R}$, between duplicate chains. Goodness of fit was assessed using posterior predictive checks and calculating Bayesian P -values. Lack of fit is evident for values falling outside of 0.05 and 0.95 (Kéry 2010).

TABLE 2 Definitions of variables measured or calculated during detection dog surveys of scat in Florida, USA, between August 2021 and October 2022.

Variable	Definition
Habitat Type	
Open field	Transect within an open, grassy field
Open canopy forest	Transect with open canopy and midstory and a dense understory
Closed canopy forest	Transect with a dense canopy and midstory and an open understory
Trail	Transect that follows a 3-m wide trail through an area that had both open and closed canopy conditions.
Scat conditions	
Scat placement	Because all transects are aligned from west to east, placement of the scat is either north or south of the transect.
Scat age	The number of times a scat was reused during the study, up to 10x
Basal area	A metric of tree stand density around the placed scat, measured with a basal area prism
Vegetation obstruction	A metric of understory density around the placed scat, measured with a Robel pole from the cardinal directions
Canopy cover	A metric of canopy closure, measured as a percentage of canopy covered by foliage with a sighting tube
Weather conditions	
Average wind speed	The mean value of wind speed measured before and after a survey using the wind speed gauge of a Kestrel unit
Average temperature	The mean value of the ambient temperature measured before and after a survey using the thermometer of a Kestrel unit
Average humidity	The mean value of the ambient humidity measured before and after a survey using data from the nearest weather station
Convection	The mean value of the convection rating (1 [lowest]–4 [highest]) calculated from measurements of sun angle, solar insolation, and wind speed taken before and after a survey
Survey conditions	
Search order	The daily survey order assigned to a transect (i.e., 1, 2, 3, or 4)
Wind working direction	Categorized as either 1: the dog was working into the wind or the wind was moving in multiple directions, or 0: the dog was working in the same direction as the wind or there was no wind
Average moving speed	The mean speed of movement of the detection dog during a survey calculated from the survey tracks recorded by the GPS unit
Year	The year in which the survey was conducted (i.e., 2021 or 2022)

In our second set of analyses, overall and habitat-specific sweep widths were obtained through nonlinear models estimating decay constants based on an exponential decay curve, $g(\gamma, \sigma) = e^{-\sigma\gamma}$, where σ is the exponential decay constant, and γ is the distance from the path (Frost 2000, Ward et al. 2016). We used 1-m interval distances in the nonlinear models and estimated the decay constant and 95% bootstrapped confidence intervals using the proportions of detections at each distance (Appendix A). Sweep widths were calculated as 2 divided by the decay constants.

Lastly, linear regression models were used to assess the effect of a suite of habitat and weather variables on the search time of the detection dog. Our dependent variable, average search time per scat, was calculated as the total move time per transect divided by the number of scats searched for per transect. Variables assessed in the models included the average temperature, humidity, wind speed, and convection during the transect (i.e., changed with each survey), a categorical variable of habitat type (open field, open canopy forest, closed canopy forest, and trail), and habitat specific covariates (i.e., remained constant across all surveys) including average vegetation obstruction, percent canopy cover, and basal area (m^2/ha). A single variable was included in each model as we had no *a priori* hypotheses of additive effects, and multicollinearity existed among some continuous covariates based on Pearson correlation coefficients ($r > 0.60$). Model fit was confirmed through residual diagnostic plots and variables whose 95% confidence intervals did not overlap 0 were considered significant predictors of average search time. Post-hoc pairwise comparisons using the emmeans package (Lenth et al. 2023) with the Tukey adjustment were used to determine differences between the means of categorical predictors.

RESULTS

We conducted 28 surveys in each of the 4 transects (112 total surveys) between 31 August 2021 and 7 October 2022. Weather conditions during surveys varied, with an average temperature of $29.4^\circ\text{C} \pm 0.4$ (16.6–37.0), wind speed of $0.5 \text{ m/s} \pm 0.3$ (0.0–1.2), humidity of $76\% \pm 1.3$ (43–98), and convection of 2.2 ± 0.1 (1–4). We placed a total of 384 scats across all transects, with each transect receiving either 97 or 95 scats. The detection dog located 66% (252 of 384) of all scats placed throughout the study.

The probability of detection models converged with parameter $\hat{R}$ values less than 1.1 and Bayes P -values indicating appropriate fit of all models. We found that none of the variables influenced detection probability of scat, as all credibility intervals overlapped zero (Table 3). Detection declined with the distance from the transect line (Figure 3).

The nonlinear sweep-width models resulted in an estimated sweep width of 49 m (95% CI = 40, 60) across all habitats, with a decay constant of $\sigma = 0.041$ (95% CI = 0.033, 0.050). Habitat-specific sweep widths exhibited high variability due to small sample sizes and high detections at each 1-meter interval and bootstrapped confidence intervals overlapped 0 for all habitats (Table 4). For these reasons, we were not able to make meaningful comparisons of sweep widths between habitats.

The search time analysis indicated that the average search time per scat was 2.23 ± 0.67 SD min (min–max = 1.10–3.84 min) and was not affected by weather covariates. However, 3 habitat variables did affect average search time: habitat type, vegetation obstruction, and average basal area. Post hoc tests revealed significantly longer search times for the closed canopy forest habitat when compared to the open field and trail habitats, with an average predicted search time for the closed canopy forest habitat of 2.54 min (95% CI = 2.30, 2.78). The open canopy forest, open field and trail habitats were predicted at 2.35 min (95% CI = 2.12, 2.60), 2.03 min (95% CI = 1.79, 2.27), and 1.98 min (95% CI = 1.74, 2.22), respectively (Figure 4A). Average search time also increased with the vegetation obstruction and average basal area of a transect. Predicted search time at the lowest vegetation obstruction score of 10 was 2.12 min (95% CI = 1.97, 2.28) and at the highest score of 100 was 2.74 min (95% CI = 2.27, 3.21; Figure 4B). Predicted search times ranged from 1.99 min (95% CI = 1.76, 2.21) at the lowest average basal area of 0 m^2/ha and increased to 2.57 min (95% CI = 2.27, 2.85) at the highest average basal area of 25 m^2/ha (Figure 4C).

DISCUSSION

Our study is one of few that have assessed how variation in vegetation structure affects the efficacy of conservation detection dog surveys. Contrary to our hypothesis, we did not find an effect of vegetation structure on detection probability. However, search time increased with greater vegetation obstruction, higher basal area, and in

TABLE 3 Estimates of mean, standard deviation (SD), and 95% credibility intervals for log-linear probability of detection models for detection dog surveys of scat conducted between August 2021 and October 2022 in Florida, USA. Results of the log-linear models were used within the exponential decay model: $p_i = \exp(-\lambda_i * \text{distance}_i)$ represented by λ . All categorical variables were dummy coded, * denotes what category is represented by the intercept.

Model	Variable	Mean	SD	2.5%	97.5%
Intercept only					
	Intercept	-3.19	0.10	-3.39	-3.00
	Trial (random effect)	0.30	0.16	0.08	0.65
Habitat type					
	Intercept	-3.32	0.20	-3.73	-2.94
	Open field	0.18	0.27	-0.36	0.72
	Open canopy forest	0.32	0.27	-0.21	0.86
	Closed canopy forest	-0.05	0.28	-0.61	0.50
	Trial (random effect)	0.31	0.16	0.08	0.67
	* Trail = 0				
Scat placement					
	Intercept	-3.25	0.13	-3.52	-3.00
	Scat placement	0.13	0.18	-0.23	0.49
	Trial (random effect)	0.30	0.16	0.08	0.65
	* South = 0				
Vegetation obstruction					
	Intercept	-3.19	0.10	-3.40	-3.01
	Vegetation obstruction	-0.003	0.004	-0.01	0.004
	Trial (random effect)	0.31	0.16	0.08	0.67
Wind					
	Intercept	-3.03	0.14	-3.32	-2.77
	Wind speed	0.11	0.31	-0.49	0.72
	Wind working direction	-0.30	0.20	-0.69	0.08
	Trial (random effect)	0.33	0.17	0.08	0.71
Canopy cover					
	Intercept	-3.20	0.10	-3.41	-3.01
	Canopy cover	0.31	0.25	-0.17	0.81
	Trial (random effect)	0.32	0.17	0.08	0.70
Basal area					
	Intercept	-3.19	0.10	-3.40	-3.01
	Basal area	0.001	0.003	-0.004	0.006
	Trial (random effect)	0.31	0.16	0.08	0.67

TABLE 3 (Continued)

Model	Variable	Mean	SD	2.5%	97.5%
Scat age	Intercept	-3.18	0.10	-3.38	-2.99
	Scat age	-0.03	0.03	-0.09	0.02
	Trial (random effect)	0.29	0.15	0.08	0.64
Search order	Intercept	-3.19	0.10	-3.40	-3.01
	Search order	-0.07	0.09	-0.24	0.10
	Trial (random effect)	0.30	0.16	0.08	0.66
Average temperature	Intercept	-3.19	0.10	-3.40	-3.01
	Temperature	0.02	0.02	-0.03	0.06
	Trial (random effect)	0.31	0.16	0.08	0.67
Average convection	Intercept	-3.19	0.10	-3.40	-3.01
	Convection	0.03	0.14	-0.25	0.31
	Trial (random effect)	0.31	0.16	0.08	0.67
Average humidity	Intercept	-3.20	0.10	-3.41	-3.02
	Humidity	0.01	0.01	-0.001	0.03
	Trial (random effect)	0.30	0.16	0.08	0.65
Moving speed	Intercept	-3.19	0.10	-3.39	-3.00
	Moving speed	0.04	0.07	-0.10	0.18
	Trial (random effect)	0.30	0.16	0.08	0.66
Year	Intercept	-3.20	0.15	-3.51	-2.92
	Moving time	0.02	0.19	-0.36	0.40
	Trial (random effect)	0.31	0.16	0.08	0.67

closed canopy forests compared to more open conditions. Although the detection dog was able to detect the same number of scats regardless of vegetation structure, some survey conditions required a longer survey period, potentially impacting time and cost constraints inherent in conservation research. As expected, detection probability decreased with increasing distance from the transect, indicating that the detection dog's ability to detect scat is not equally distributed across the sweep width and diminishes further from the transect. Additionally, we did not detect a difference in detection probability between surveys conducted on-trail and off-trail and surveys on-trail were performed faster than those in closed canopy forest conditions.

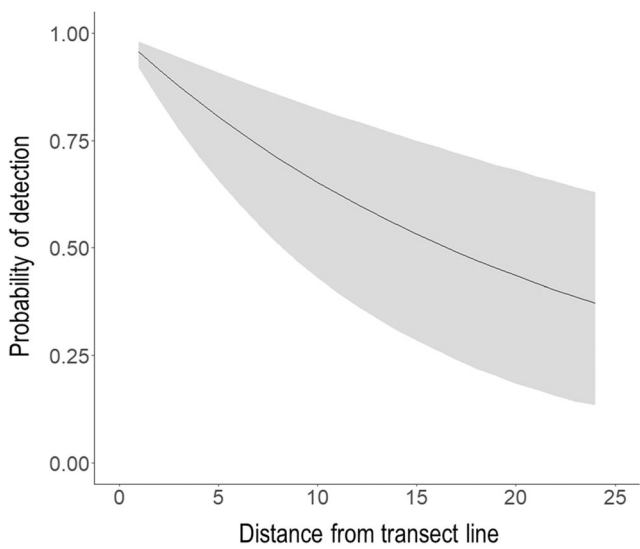


FIGURE 3 Predicted probability of detection with increasing distance from transect line from intercept-only detection probability model for a scat detecting dog. Grey bands represent 95% predicted credibility intervals. Detection dog surveys were conducted between August 2021 and October 2022 in Florida, USA.

TABLE 4 Sweep widths and decay constants (σ) calculated across all habitats and within each habitat from detection dog surveys of scat conducted between August 2021 and October 2022 in Florida, USA. Habitat-specific sweep widths exhibited high variability due to small sample sizes at each 1-meter interval and bootstrapped confidence intervals overlapped 0 for all habitats.

Transect	Sweep width (m) (95% CI)	Decay constant (σ) (95% CI)
All habitats	49 (40–60)	0.041 (0.033–0.050)
Open field	50 (33–80)	0.040 (0.025–0.060)
Open canopy forest	35 (25–51)	0.057 (0.040–0.081)
Closed canopy forest	49 (31–79)	0.041 (0.025–0.065)
Trail	75 (47–147)	0.026 (0.014–0.043)

Over the 200 m transect, the detection dog was able to locate scats equally well in all habitat conditions. However, similar to Leigh and Dominick (2015), the mean search time was longer for surveys in the closed canopy forest transect than for those in the open field and trail transects. When working on-lead in the closed canopy forest transect, the handler often had to stop to maneuver through and around many vines, trees, and shrubs, potentially interrupting the detection dog's search and increasing the time necessary to locate a scat. Search time also increased with higher vegetation obstruction and basal area. Increases in vegetation obstruction may have slowed the detection dog's search, as vegetation has the potential to interrupt the scent cone of vapor molecules emanating from the target and reduce the distance the scent can travel or cause the scent to pool or swirl (Syrotuck 1972, Rebmann et al. 2000, MacKay et al. 2008). Although increasing basal area contributed to increased search time, surveys conducted on the trail transect were significantly faster than searches in the closed canopy transect despite having similar average basal area.

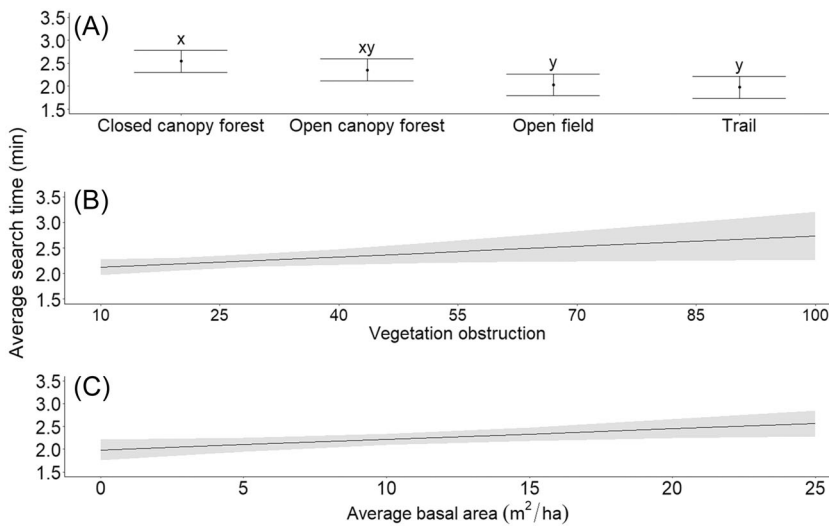


FIGURE 4 Supported models describing the influence of habitat type (A), vegetation obstruction (B), and average basal area (C) on the average search time per scat in a transect for a scat detection dog. In panel A, dots represent the mean predictions for each habitat type and error bars represent 95% confidence intervals. Significant differences for pairwise comparisons are denoted by non-matching letters (x and y; $\alpha = 0.05$). In panel B and panel C, solid lines represent the mean prediction of average search time for each average vegetation obstruction value and average basal area value and the grey-shaded area represents the 95% confidence intervals around the predictions. Detection dog surveys were conducted between August 2021 and October 2022 in Florida, USA.

Because trail searches were performed faster and detection probability did not differ, trail surveys may be a viable search method for detection dog surveys. The sweep width within trail surveys was also the largest, albeit with the widest confidence interval as well. Trail surveys are likely to be beneficial when off-trail surveys would be cost-prohibitive (e.g., time necessary to survey off-trail) or when habitat conditions are too dense to navigate. Surveying along a trail requires less energy and may extend the timeframe a dog can work, as searching through thick, vegetated areas is only necessary when a target scent is detected. Additionally, trail surveys may increase detections for certain species, as many animals use trails, unpaved roads, or game trails to travel (Cusack et al. 2015, Tanwar et al. 2021). Trail surveys could be particularly useful for studies with limited information about the occurrence and habitat associations of rare or cryptic species, as they allow for quick coverage of large areas and can help guide more intensive off-trail surveys. However, trail surveys may not be as successful in areas that are highly trafficked by people and pets or when the target species avoids trails (Cusack et al. 2015, Willcox et al. 2019). Additionally, studies relying solely on trail surveys may create biases, as only habitats and properties with trails can be surveyed.

Our study determined that for a small scat, such as that of a mink, the sweep width of our detection dog working on-lead was 49 m (i.e., 24.5 m on either side of the transect). After this distance, the dog's ability to locate the target scat declined rapidly. However, when determining the sweep width of a detection dog, ideally 50% of all scats placed would be missed by the detection dog (Koopman 1946, 1980). Because of logistical constraints and the success of our detection dog, we were not able to reach this number and our dog only missed 34% of all scats. This likely contributed to the larger confidence intervals we observed when estimating sweep widths. Other studies attempting to assess sweep width have faced similar issues, where the detection dog simply does not miss enough target scats (Cristescu et al. 2015). It can also be difficult to compare sweep widths between studies with different targets, as they will have varying degrees of potency (i.e., concentration of vapor molecules) that affect the detection distance (Syrotuck 1972, Woollett et al. 2015). A sweep width of 16.8 m was reported for detection dogs

searching for rat carcasses (Glen et al. 2018) and 95 m for detection dogs searching for human targets (Chiacchia et al. 2015). Few studies have directly reported sweep widths—possibly because of the extensive time and effort necessary to achieve an adequate sample size and miss rate—instead reporting only a summary of detection distances. Sweep width calculations provide valuable guidance for survey design, establishing the minimum distance between transects to achieve complete coverage of an area.

Our study could not assess all scenarios that a detection dog may encounter during a survey and therefore detection probability may be affected by variables we did not account for. Field scenarios are likely to cover greater distances (e.g., $\geq 2,000$ m in many surveys) compared to our surveys (200 m) and scats may be aged or degraded by the weather. Over greater distances, factors like temperature and vegetation may be more tiring on the dog and could reduce the probability of detecting the target. Additionally, the probability of detection would likely decrease with increasing scat age and exposure to environmental conditions. Small mammals and insects frequently disturb scats under normal field conditions (Sanchez et al. 2004, Stanbrook and King 2022), especially in the warmer months (Sanchez et al. 2004), which could reduce the concentration of vapor molecules for a particular scat. Future studies should evaluate the effect of habitat and weather conditions on detection probability over longer distances and consider potential scat degradation to reflect real-world scenarios. However, care should always be taken to monitor the health of the dog and not work in high temperatures for extended periods.

The results of this study reflect the performance of a single dog and handler team and therefore may not be representative of all detection dog teams in all conditions. Several studies have reported that search performance (e.g., successful finds, false alerts, search time) can vary by dog characteristics (e.g., individual dog, dog breed, dog personality), target scents, handler, and search areas (e.g., habitat, indoors or outdoors; Reed et al. 2011, Jezierski et al. 2014, Beebe et al. 2016). Our detection dog team had experience working in remote wilderness areas ranging from open beaches to densely vegetated forests prior to conducting these surveys. Previous exposure to a wide range of survey conditions may have contributed to our detection dog's ability to perform equally well across all transects. We recommend each detection dog team ideally conduct controlled trials mimicking realistic search scenarios to observe the actual performance of their dog and handler. Further, additional research into detection probability and sweep width in various habitat conditions by multiple detection dog teams is necessary to develop a more complete understanding about the impacts of vegetation structure on detection probability and lead to improved study design.

Lastly, we'd like to reiterate that our study involved working a dog on-lead and therefore may not be directly applicable to studies working a dog off-lead. Working a dog on-lead may reduce the sweep width and limit the vegetation conditions that can be surveyed (e.g., dense brush where the lead is likely to get tangled; MacKay et al. 2008, Woollett et al. 2015). However, few studies have compared the effectiveness of detection dogs working on- and off-lead and results were largely inconclusive (Cristescu et al. 2015). Detection dogs working on-lead are capable of effectively locating targets, but additional research comparing the performance of on- and off-lead detection dogs in various habitats would improve our understanding of how protocols may need to be modified in each circumstance.

Detection dogs are a valuable tool when searching for rare or cryptic wildlife species and understanding sweep width, detection probability, and search time can vastly improve study design. Given adequate time, our detection dog performed equally well across a variety of habitats and weather conditions, and therefore provides evidence that in real-world applications, surveys conducted by our dog and handler team at differing sites should be spatially and temporally unbiased. Future researchers should consider how habitat conditions may affect the necessary survey time when planning and budgeting for detection dog surveys in conservation research. Our study also provides support for the use of on-trail surveys as a viable alternative to off-trail surveys, especially when searching dense areas or as an initial survey option before developing more intensive and time-consuming surveys. Although the probability of detection and sweep width will vary by target species and by each detection dog team, our study contributes to our growing understanding of the capabilities and limitations of detection dogs in wildlife research.

ACKNOWLEDGMENTS

We would like to thank T. Goebel at Zoo Montana and R. Malstaff at the San Antonio Zoological society for assisting in the collection of scat used during these trials, Newnan's Lake Conservation Area and the Rotary Club of Gainesville for allowing site access, S. Hogan and E. Braun for their assistance in the field, and L. Braun, J. Borkholder, and 2 anonymous reviewers for their constructive comments that greatly improved this manuscript. And of course, thank you to Cowboy, our detection dog, for his endless energy and effort and without whom none of this would be possible.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

ETHICS STATEMENT

All data collection activities were in accordance with FWC protocols regarding animal welfare and human safety. The authors have no conflict of interest to declare.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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REFERENCES

- Baxter, P. W. J., and H. P. Possingham. 2011. Optimizing search strategies for invasive pests: learn before you leap. *Journal of Applied Ecology* 48:86–95.
- Beebe, S. C., T. J. Howell, and P. C. Bennett. 2016. Using scent detection dogs in conservation settings: a review of scientific literature regarding their selection. *Frontiers in Veterinary Science* 3:96.
- Cablk, M. E., J. C. Sagebiel, J. S. Heaton, and C. Valentin. 2008. Olfaction-based detection distance: a quantitative analysis of how far away dogs recognize tortoise odor and follow it to source. *Sensors* 8:2208–2222.
- Cablk, M. E., and J. S. Heaton. 2006. Accuracy and reliability of dogs in surveying for desert tortoise (*Gopherus agassizii*). *Ecological Applications* 16:1926–1935.
- Cacho, O. J., S. Hester, and D. Spring. 2007. Applying search theory to determine the feasibility of eradicating an invasive population in natural environments. *Australian Journal of Agricultural and Resource Economics* 51:425–443.
- Chiacchia, K. B., H. E. Houlahan, and R. S. Hostetter. 2015. Deriving effective sweep width for air-scent dog teams. *Wilderness & Environmental Medicine* 26:142–149.
- Criscescu, R. H., E. Foley, A. Markula, G. Jackson, D. Jones, and C. Frère. 2015. Accuracy and efficiency of detection dogs: a powerful new tool for koala conservation and management. *Scientific Reports* 5:8329.
- Cusack, J. J., A. J. Dickman, J. M. Rowcliffe, C. Carbone, D.W. Macdonald, and T. Coulson. 2015. Random versus game trail-based camera trap placement strategy for monitoring terrestrial mammal communities. *PLOS ONE* 10(5):e0126373.
- DeMatteo, K. E., M. A. Rinas, C. F. Argüelles, B. E. Holman, M. S. Di Bitetti, B. Davenport, P. G. Parker, and L. S. Eggert. 2014. Using detection dogs and genetic analyses of scat to expand knowledge and assist felid conservation in Misiones, Argentina. *Integrative Zoology* 9:623–639.
- DeMatteo, K. E., M. A. Rinas, M. M. Sede, B. Davenport, C. F. Argüelles, K. Lovett, and P. G. Parker. 2009. Detection dogs: an effective technique for bush dog surveys. *The Journal of Wildlife Management* 73:1436–1440.
- Emlen, J. T. 1967. A rapid method for estimating arboreal canopy cover. *Ecology* 48:158–160.
- Florida Natural Areas Inventory. 2010. Guide to the natural communities of Florida: 2010 edition. Florida Natural Areas Inventory, Tallahassee, Florida, USA. <<https://www.fnai.org/species-communities/natcom-guide>>. Accessed 11 Aug 2021.
- Frost, J. R. 2000. Principles of search theory. Colorado Search and Rescue Board, Denver, USA. <<https://studylib.net/doc/18804540/principles-of-search-theory-colorado-search-and-rescue-...>>. Accessed 11 Aug 2021.
- Ganey, J. L., and W. M. Block. 1994. Technical note: a comparison of two techniques for measuring canopy closure. *Western Journal of Applied Forestry* 9:21–23.

- Gelman, A., J. B. Carlin, H. S. Stern, D. B. Dunson, A. Vehtari, and D. B. Rubin. 2013. Bayesian data analysis. CRC press, Boca Raton, Florida, USA.
- Glen, A. S., J. C. Russell, C. J. Veltman, and R. M. Fewster. 2018. I smell a rat! Estimating effective sweep width for searches using wildlife-detector dogs. *Wildlife Research* 45:500–504.
- Glen, A. S., and C. J. Veltman. 2018. Search strategies for conservation detection dogs. *Wildlife Biology* 2018:wlb.00393.
- Gorman, M. L., and B. J. Trowbridge. 1989. The role of odor in the social lives of carnivores. Pages 57–88 in J. L. Gittleman, editor. *Carnivore behavior, ecology, and evolution*. Cornell University Press, Ithaca, New York, USA.
- Graham, H. 1994. Probability of detection for search dogs or how long is your shadow? *Response Magazine* Winter, 1–7. National Association for Search and Rescue, Centreville, Virginia, USA.
- Hauser, C. E., K. M. Giljohann, M. A. McCarthy, G. E. Garrard, A. P. Robinson, N. S. Williams, and J. L. Moore. 2022. A field experiment characterizing variable detection rates during plant surveys. *Conservation Biology* 36(3):e13888.
- Jeziarski, T., E. Adamkiewicz, M. Walczak, M. Sobczyńska, A. Górecka-Bruzda, J. Ensminger, and L. E. Papet. 2014. Efficacy of drug detection by fully-trained police dogs varies by breed, training level, type of drug and search environment. *Forensic Science International* 237:112–118.
- Kellner, K. 2015. jagsUI: a wrapper around rjags to streamline JAGS analyses. R package version, 1(1). <<https://cran.r-project.org/web/packages/jagsUI/index.html>>. Accessed 06 July 2023.
- Kéry, M. 2010. Introduction to WinBUGS for ecologists: bayesian approach to regression, ANOVA, mixed models and related analyses. Academic Press, New York, NY, USA.
- Koopman, B. O. 1980. Search and screening: general principles with historical applications. Pergamon Press, New York, New York, USA.
- Koopman, B. O. 1946. Search and Screening. Operations Evaluation Group Report No. 56, Washington, D.C., USA. <<https://www.loc.gov/resource/gdcmassbookdig.searchscreening56koop/?st=pdf&pdf>>. Accessed 28 Jul 2021.
- Leigh, K. A., and M. Dominick. 2015. An assessment of the effects of habitat structure on the scat finding performance of a wildlife detection dog. *Methods in Ecology Evolution* 6:745–752.
- Lenth, R.V., P. Buurkner, M. J. Herve, M. Jung, J. Love, F. Miguez, H. Riebl, and H. Singmann. 2023. emmeans: estimated Marginal Means, aka Least-Squares Means. version 1.8.6. <<https://CRAN.R-project.org/package=emmeans>>. Accessed 06 July 2023.
- Long, R.A., T. M. Donovan, P. MacKay, W. J. Zielinski, and J. S. Buzas. 2011. Predicting carnivore occurrence with noninvasive surveys and occupancy modeling. *Landscape Ecology* 26:327–340.
- Long, R. A., T. M. Donovan, P. Mackay, W. J. Zielinski, and J. S. Buzas. 2007a. Comparing scat detection dogs, cameras, and hair snares for surveying carnivores. *The Journal of Wildlife Management* 71:2018–2025.
- Long, R. A., T. M. Donovan, P. Mackay, W. J. Zielinski, and J. S. Buzas. 2007b. Effectiveness of scat detection dogs for detecting forest carnivores. *The Journal of Wildlife Management* 71:2007–2017.
- MacKay, P., D. A. Smith, R. A. Long, and M. Parker. 2008. Scat detection dogs. Pages 183–222 in R. A. Long, P. MacKay, W. J. Zielinski, and J. C. Ray, editors. *Noninvasive survey methods for carnivores*. Island Press, Washington, D.C., USA.
- Myers, R., and J. Ewel. 1990. *Ecosystems of Florida*. University Press of Florida, Gainesville, USA.
- Nussey, K. E., T. Esque, J. Heaton, M. Cablk, K. Drake, C. Valentin, J. Yee, and P. Medica. 2008. Are wildlife detector dogs or people better at finding desert tortoises (*Gopherus agassizii*). *Journal of Herpetological Conservation and Biology* 3: 103–115.
- Osterkamp, T. 2020. Detector dogs and scent movement. CRC Press, Boca Raton, Florida, USA.
- QGIS.org. 2020. QGIS Geographic Information System. Open Source Geospatial Foundation Project. <<http://qgis.osgeo.org>>. Accessed 1 October 2020.
- R Core Team. 2020. R: a language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.
- Rebmann, A., E. David, and M. Sorg. 2000. Cadaver dog handbook: forensic training and tactics for the recovery of human remains. CRC Press, Boca Raton, Florida, USA.
- Reed, S. E., A. L. Bidlack, A. Hurt, and W. M. Getz. 2011. Detection distance and environmental factors in conservation detection dog surveys. *The Journal of Wildlife Management* 75:243–251.
- Richardson, J. H. 1958. Comparative efficiency of the wedge prism method and the circular plot method in estimating volumes of Douglas-Fir stands. Thesis, Oregon State College, Corvallis, USA.
- Robel, R. J., J. N. Briggs, A. D. Dayton, and L. C. Hulbert. 1970. Relationships between visual obstruction measurements and weight of grassland vegetation. *Journal of Range Management* 23:295–297.
- Sanchez, D. M., P. R. Krausman, T. R. Livingston, and P. S. Gipson. 2004. Persistence of carnivore scat in the Sonoran Desert. *Wildlife Society Bulletin* 32:366–372.
- Smith, D. A., K. Ralls, B. L. Cypher, and J. E. Maldonado. 2005. Assessment of scat-detection dog surveys to determine kit fox distribution. *Wildlife Society Bulletin* 33:897–904.

- Stanbrook, R., and J. R. King. 2022. Dung beetle community composition affects dung turnover in subtropical US grasslands. *Ecology and Evolution* 12(2):e8660.
- Syrotuck, W. G. 1972. *Scent and the scenting dog*. Arner Publishing, Rome, New York, USA.
- Tanwar, K. S., A. Sadhu, and Y. V. Jhala. 2021. Camera trap placement for evaluating species richness, abundance, and activity. *Scientific Reports* 11:23050.
- Tom, B. M. 2012. A comparison of noninvasive survey methods for monitoring mesocarnivore populations in Kentucky. Thesis, University of Kentucky, Lexington, USA.
- Ward, D. F., D. P. Anderson, and M. C. Barron. 2016. Using spatially explicit surveillance models to provide confidence in the eradication of an invasive ant. *Scientific Reports* 6:34953.
- Warren, W. G. 1960. Measurement of stand basal area with optical wedges. New Zealand Forestry Research Notes Technical Paper No. 33, Wellington, New Zealand.
- Wasser, S. K., B. Davenport, E. R. Ramage, K. E. Hunt, M. Parker, C. Clarke, and G. Stenhouse. 2004. Scat detection dogs in wildlife research and management: application to grizzly and black bears in the Yellowhead Ecosystem, Alberta, Canada. *Canadian Journal of Zoology* 82:475–492.
- Wasser, S. K., L. S. Hayward, J. Hartman, R. K. Booth, K. M. Broms, J. Berg, E. Seely, L. Lewis, and H. Smith. 2012. Using detection dogs to conduct simultaneous surveys of northern spotted (*Strix occidentalis caurina*) and barred owls (*Strix varia*). *PLOS ONE* 7(8):e42892.
- Willcox, D., H. C. Nash, S. Trageser, H. J. Kim, L. Hywood, E. Connelly, G. Ichu Ichu, J. Kambale Nyumu, C. L. Mousset Moumbolou, D. J. Ingram et al. 2019. Evaluating methods for detecting and monitoring pangolin (Pholidata: Manidae) populations. *Global Ecology and Conservation* 17:e00539.
- Woollett (Smith), D. A., A. Hurt, and N. L. Richards. 2015. The current and future roles of free-ranging detection dogs in conservation efforts. Pages 239–264 in M. E. Gompper, editor. *Free-ranging dogs and wildlife conservation*. Oxford Academic, online edition.

Associate Editor: Lucas Hall.

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How to cite this article: Hassler, K. N., A. L. Sylvia, and L. M. Smith. 2024. Trail vs. thicket: evaluating conservation detection dog performance in varied terrain. *Wildlife Society Bulletin* 48:e1558.
<https://doi.org/10.1002/wsb.1558>

APPENDIX A: DISTRIBUTION OF RANDOMIZED SCAT PLACEMENT

See Table A1.

TABLE A1 Overall and habitat-specific numbers of detections and nondetections of mink scat placed at varying distances from the transect line searched by the detection dog in Florida, USA, between August 2021 and October 2022. The first value denotes the overall number of detections and nondetections and values in parenthesis denote detections and nondetections for closed canopy forest, open field, open canopy forest, and trail habitats. *A single scat was placed at 24.0 m during the study and was included in the 23-m calculations.

Distance (m)	Number of detections (closed canopy forest, open field, open canopy forest, trail)	Number of nondetections (closed canopy forest, open field, open canopy forest, trail)	Total scat placed
0	12 (1, 1, 6, 4)	4 (2, 0, 2, 0)	16
1	13 (5, 3, 4, 1)	2 (0, 0, 0, 2)	15
2	10 (5, 2, 2, 1)	3 (1, 0, 1, 1)	13
3	17 (5, 4, 2, 6)	8 (1, 3, 3, 1)	25
4	16 (2, 6, 3, 5)	5 (1, 4, 0, 0)	21
5	20 (7, 2, 4, 7)	6 (3, 1, 0, 2)	26
6	20 (6, 5, 6, 3)	4 (1, 0, 0, 3)	24
7	9 (4, 3, 1, 1)	1 (0, 0, 1, 0)	10
8	14 (2, 2, 4, 6)	4 (1, 1, 1, 1)	18
9	15 (2, 7, 3, 3)	6 (1, 0, 2, 3)	21
10	15 (2, 5, 4, 4)	15 (2, 5, 6, 2)	30
11	15 (5, 2, 5, 3)	4 (1, 1, 1, 1)	19
12	9 (5, 1, 2, 1)	8 (0, 0, 3, 5)	17
13	8 (1, 1, 5, 1)	5 (0, 1, 2, 2)	13
14	10 (3, 5, 1, 1)	6 (3, 1, 0, 2)	16
15	11 (2, 4, 2, 3)	5 (1, 0, 3, 1)	16
16	3 (1, 0, 1, 1)	6 (3, 3, 0, 0)	9
17	6 (2, 1, 2, 1)	4 (1, 2, 1, 0)	10
18	9 (3, 1, 1, 4)	6 (0, 1, 3, 2)	15
19	5 (0, 0, 1, 4)	4 (0, 3, 1, 0)	9
20	1 (0, 0, 0, 1)	6 (1, 3, 1, 1)	7
21	3 (0, 0, 0, 3)	3 (1, 1, 1, 0)	6
22	8 (4, 1, 3, 0)	7 (3, 2, 2, 0)	15
23*	3 (1, 1, 0, 1)	10 (2, 3, 4, 1)	13